Extracting azimuthal Fourier moments from sparse data

- Hermes data is always statistics-limited, because we always want to extract kinematic distributions in finer bins or more dimensions
 - ⇒ Azimuthal Fourier moments must be extracted from sparse distributions containing bins with non-Gaussian statistics
- The acceptance can (and does!) cause a substantial systematic bias on observables extracted while integrating over kinematic variables on which that observable strongly depends. Examples:
 - P_t -weighted transverse target spin asymmetries
 - DVCS beam charge asymmetries (see next page)
 - ⇒ Quantify ignorance of full kinematic dependence, propagate to result
 - \Rightarrow fit the full kinematic dependence on (x,y,z,P_t) using some standard set of 4D orthogonal functions, then fold with known $\sigma_{uu}(x,y,z,P_t)$

Covariance matrix of fitted coefficients is propagated through folding

Maximum-Likelihood fit: unpol. example

For ML fit of unpol. azimuthal moments, the event dist'n and PDF are

$$CN(x,y,z,P_{t},\phi,\phi_{S}) = \varepsilon(x,y,z,P_{t},\phi,\phi_{S})\underline{\sigma}_{UU}(x,y,z,P_{t}) \times \left[1 + A_{UU}^{\cos\phi}(\lambda_{1},x,y,z,P_{t})\cos\phi + A_{UU}^{\cos2\phi}(\lambda_{2},x,y,z,P_{t})\cos(2\phi)\right]$$

$$\equiv F_{UU}(\lambda_{1},\lambda_{2},x,y,z,P_{t},\phi,\phi_{S}) \text{ (Probability Density Fun.)}$$

Maximize Likelihood with respect to

parameter sets
$$\lambda_1, \lambda_2$$
: $\mathcal{L}(\lambda_1, \lambda_2) = \frac{\prod_{i=1}^{N_x} F_{UU}(\lambda_1, \lambda_2, x_i, y_i, z_i, P_{ti}, \phi_i, \phi_{Si})}{\mathcal{N}_{UU}^{N_x}(\lambda_1, \lambda_2)}$

The denominator fixes the normalization of the PDF as the parameter sets λ_1 and λ_2 are stepped in the fit search:

$$\mathcal{N}_{UU}(\lambda_1, \lambda_2) = \int dx dy dz dP_t d\phi d\phi_S F_{UU}(\lambda_1, \lambda_2, x, y, z, P_t, \phi, \phi_S)$$

Acceptance ϵ and azimuthally averaged cross section $\underline{\sigma}_{\it uu}$ do not depend on the fitting parameter sets λ_1 and λ_2

> they can be omitted in calculation of the numerator!!

How can we conveniently evaluate the normalization integral?

PDF Normalization: unpolarized case

Probability Density Function normalization:

$$\mathcal{N}_{UU}(\lambda_{1}, \lambda_{2}) = \int dx dy dz dP_{t} d\phi d\phi_{S} \, \boldsymbol{\varepsilon}(x, y, z, P_{t}, \phi, \phi_{S}) \, \underline{\sigma}_{UU}(x, y, z, P_{t}) \times \left[1 + A_{UU}^{\cos\phi}(\lambda_{1}, x, y, z, P_{t}) \cos\phi + A_{UU}^{\cos2\phi}(\lambda_{2}, x, y, z, P_{t}) \cos(2\phi) \right]$$

Solution:

Use Monte Carlo integration method with azimuthal event weights. As Pythia MC events are distributed according to $\varepsilon_{\sigma_{\nu\nu}}$, PDF integral is

$$\mathcal{N}_{UU}(\lambda_1, \lambda_2) = \sum_{j=1}^{N_{MC}} W_j^{MC} \left[1 + A_{UU}^{\cos\phi}(\lambda_1, x_j, y_j, z_j, P_{tj}) \cos\phi_j + A_{UU}^{\cos2\phi}(\lambda_2, x_j, y_j, z_j, P_{tj}) \cos(2\phi_j) \right]$$

For efficiency:

All factors in both likelihood product (expt'l events) and integral sum (MC events) can be tabulated for all events before starting the fit search

Result of the fit

$$\sigma_{UU}(x, y, z, P_t, \phi) = \underline{\sigma}_{UU}(x, y, z, P_t) \times \left[1 + A_{UU}^{\cos \phi}(\lambda_1, x, y, z, P_t) \cos \phi + A_{UU}^{\cos 2\phi}(\lambda_2, x, y, z, P_t) \cos(2\phi) \right]$$

The parameter sets λ_1 and λ_2 could be archived in the Durham data base, but we compare models to asymmetries in yields integrated over some variables:

$$\langle \cos \phi \rangle_{UU}^{h}(x) = \frac{\int dy dz dP_{t} \underline{\sigma}_{UU}^{Born}(x, y, z, P_{t}) A_{UU}^{\cos \phi}(\lambda_{1}, x, y, z, P_{t})}{\int dy dz dP_{t} \underline{\sigma}_{UU}^{Born}(x, y, z, P_{t})}$$

This integral can be evaluated using $\underline{\sigma}_{uu}(x,y,z,P_t)$ from parton dist. funs and measured hadron multiplities, or a Pythia MC event set generated in 4π :

$$\langle \cos \phi \rangle_{UU}^{h}(x) = \sum_{j=1}^{N_{MC}} W_j^{MC} A_{UU}^{\cos \phi}(\lambda_1, x_j, y_j, z_j, P_{tj}) / \sum_{j=1}^{N_{MC}} W_j^{MC}$$

If the parameterization is linear in the fitted parameters, it is easy to propagate their covariance matrices through this sum

Exchange unknown systematic error for well-defined statistical uncertainty

Maximum-likelihood fit: transverse-polarized case

Using the predetermined full kinematic dependence of the $\cos(n\phi)$ moments, the event distribution and PDF for target polarization dist'n $\rho(P)$, -1 < P < 1, is:

$$CN(P,x,y,z,P_{t},\phi,\phi_{S}) = \rho(P) \, \varepsilon(x,y,z,P_{t},\phi,\phi_{S}) \, \underline{\sigma}_{UU}(x,y,z,P_{t}) \times$$

$$\left\{ 1 + A_{UU}^{\cos\phi}(x,y,z,P_{t}) \cos\phi + A_{UU}^{\cos2\phi}(x,y,z,P_{t}) \cos(2\phi) + P[A_{C}(\lambda_{1},x,y,z,P_{t}) \sin(\phi+\phi_{S}) + A_{S}(\lambda_{2},x,y,z,P_{t}) \sin(\phi-\phi_{S})] \right\}$$

$$\equiv F(\lambda_{1},\lambda_{2},P,x,y,z,P_{t},\phi,\phi_{S})$$

ML treats the target polarization P like any other (e.g., kinematic) variable. Again the parameter-independent factor $\varepsilon_{\sigma_{uu}}$ can be omitted in the numerator of the Likelihood:

$$\mathcal{L}(\lambda_1, \lambda_2) = \prod_{i=1}^{N} \frac{F(\lambda_1, \lambda_2, P_i, x_i, y_i, z_i, P_{ti}, \phi_i, \phi_{Si})^{W_i}}{\mathcal{N}(\lambda_1, \lambda_2)^{W_i}}$$

Here, W_i are event weights (from e.g. RICH PId)

The product in the denominator is independent of λ_1 and λ_2 and can be ignored in the likelihood maximization, if the whole data set has no net polarization:

$$\int d\boldsymbol{P} \, \boldsymbol{P} \, \boldsymbol{\rho}(\boldsymbol{P}) = 0$$

PDF normalization: transverse-polarized case

In the PDF normalization integral, the integration over P factorizes:

$$\mathcal{N}(\lambda_{1}, \lambda_{2}) = \int dP \, dx \, dy \, dz \, dP_{t} \, d\phi \, d\phi_{S} \, \rho(P) \, \mathbf{\epsilon}(x, y, z, P_{t}, \phi, \phi_{S}) \, \underline{\sigma}_{UU}(x, y, z, P_{t}) \, \times$$

$$\left\{ 1 + A_{UU}^{\cos\phi}(x, y, z, P_{t}) \cos\phi + A_{UU}^{\cos2\phi}(x, y, z, P_{t}) \cos(2\phi) \right.$$

$$+ P \left[A_{C}(\lambda_{1}, x, y, z, P_{t}) \sin(\phi + \phi_{S}) + A_{S}(\lambda_{2}, x, y, z, P_{t}) \sin(\phi - \phi_{S}) \right] \right\}$$

$$= \int dP \rho(P) \cdot \int dx \, dy \, dz \, dP_{t} \, d\phi \, d\phi_{S} \, \mathbf{\epsilon}(x, y, z, P_{t}, \phi, \phi_{S}) \, \underline{\sigma}_{UU}(x, y, z, P_{t}) \, \times$$

$$\left\{ 1 + A_{UU}^{\cos\phi}(x, y, z, P_{t}) \cos\phi + A_{UU}^{\cos2\phi}(x, y, z, P_{t}) \cos(2\phi) \right.$$

$$+ \left. \frac{\int dP \, P \rho(P)}{\int dP \, \rho(P)} \left[A_{C}(\lambda_{1}, x, y, z, P_{t}) \sin(\phi + \phi_{S}) + A_{S}(\lambda_{2}, x, y, z, P_{t}) \sin(\phi - \phi_{S}) \right] \right\}$$

This normalization integral is obviously independent of λ_1 and λ_2 if...

$$\int dP \, P \, \rho(P) = 0$$

If necessary, this might be arranged by scaling the weights of events recorded with one polarization sign.

ML fit: DVCS beam-helicity asymmetry

The event distribution and PDF for beam polarization dist'n $\rho(P)$, -1 < P < 1, is:

$$CN(P,x,y,t,\phi) = \rho(P) \, \varepsilon(x,y,t,\phi) \, \underline{\sigma}_{UU}(x,y,t) \times$$

$$\{1 + P[A_1(\lambda_1,x,y,t) \sin(\phi) + A_2(\lambda_2,x,y,t) \sin(2\phi)]\}$$

$$\equiv F(\lambda_1,\lambda_2,P,x,y,t,\phi)$$

Again the parameter-independent factor $\varepsilon_{\sigma_{\upsilon\upsilon}}$ can be omitted in the numerator of the Likelihood:

$$\mathcal{L}(\lambda_1, \lambda_2) = \prod_{i=1}^{N} \frac{F(\lambda_1, \lambda_2, P_i, x_i, y_i, t_i, \phi_i)^{W_i}}{\mathcal{N}(\lambda_1, \lambda_2)^{W_i}}$$

Here, W_i are event weights (from e.g. RICH PId)

We will show the normalization in the denominator is independent of λ_1 and λ_2 and can therefore be ignored in the likelihood maximization if either:

-- the net target polarization for the whole data set is zero:

$$\int dP \, P \, \rho(P) = 0$$

-- or if the acceptance has no odd harmonics in ϕ :

$$\varepsilon(x, y, t, \phi) = \varepsilon(x, y, t, -\phi)$$

PDF normalization: DVCS beam-helicity case

In the PDF normalization integral, the integration over P factorizes:

$$\mathcal{N}(\lambda_{1}, \lambda_{2}) = \int dP dx dy dt d\phi \, \rho(P) \, \boldsymbol{\varepsilon}(x, y, t, \phi) \, \underline{\sigma}_{UU}(x, y, t) \times$$

$$\{1 + P[A_{1}(\lambda_{1}, x, y, t) \sin(\phi) + A_{2}(\lambda_{2}, x, y, t) \sin(2\phi)]\}$$

$$= \int dP \rho(P) \cdot \int dx dy dt d\phi \, \boldsymbol{\varepsilon}(x, y, t, \phi) \, \underline{\sigma}_{UU}(x, y, t) \times$$

$$\left\{1 + \frac{\int dP \, P \rho(P)}{\int dP \, \rho(P)} \left[A_{1}(\lambda_{1}, x, y, t) \sin(\phi) + A_{2}(\lambda_{2}, x, y, t) \sin(2\phi)\right]\right\}$$

This normalization integral is independent of λ_1 and λ_2 if either...

$$\int d\boldsymbol{P} \, \boldsymbol{P} \, \boldsymbol{\rho}(\boldsymbol{P}) = 0$$

(If necessary, this can be arranged by scaling the weights of events recorded with one polarization sign)

or if...

$$\varepsilon(x, y, t, \phi) = \varepsilon(x, y, t, -\phi)$$

because its convolution with $sin(n\phi)$ again yields zero for the second term.

Summary

- An unknown systematic error from multi-dimensional correlations between acceptance and asymmetry is exchanged for a slightly larger but wellknown statistical uncertainty
- All available information about the correlated kinematic dependence of the asymmetries can be extracted and available for formation of any projection of the result